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**IDENTIFYING CENTRAL BANK LIQUIDITY
SUPER-SPREADERS IN INTERBANK
FUNDS NETWORKS**

By

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Identifying Central Bank Liquidity Super-Spreaders in Interbank Funds Networks ^{*}

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Abstract

We model the allocation of central bank liquidity among the participants of the interbank market by using network analysis' metrics. Our analytical framework considers that a super-spreader simultaneously excels at receiving (borrowing) and distributing (lending) central bank's liquidity for the whole network, as measured by financial institutions' *hub centrality* and *authority centrality*, respectively. Evidence suggests that the Colombian interbank funds market exhibits an inhomogeneous and hierarchical network structure, akin to a core-periphery organization, in which a few financial institutions fulfill the role of central bank's liquidity *super-spreaders*. Our results concur with evidence from other interbank markets and other financial networks regarding the flaws of traditional direct financial contagion models based on homogeneous and non-hierarchical networks. Also, concurrent with literature on lending relationships in interbank markets, we confirm that the probability of being a super-spreader is mainly determined by financial institutions' size. We provide additional elements for the implementation of monetary policy and for safeguarding financial stability.

JEL: E5, G2, L14

Keywords: interbank, liquidity, monetary policy, financial stability, networks, super-spreader, central bank.

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1. Introduction

The interbank funds market plays a central role in monetary policy transmission: it allows *banks to exchange central bank money in order to share liquidity risks* (Fricke and Lux, 2014). For that reason, *they are the focus of central banks' implementation of monetary policy and have a significant effect on the whole economy* (Allen et al., 2009; p.639), whereas the interbank rate is commonly regarded as central bank's main target for assessing the effectiveness of monetary policy transmission. In addition, as there are powerful incentives for participants to monitor each other, the interbank funds market also plays a key role as a source of market discipline (Rochet and Tirole, 1996; Furfine, 2001). Thus, modeling the interaction among participants of the interbank market contributes to understand some of the recent disruptions that affected both the monetary policy transmission and the financial stability.

During the Global Financial Crisis (GFC) the interbank funds market exhibited a liquidity freezing in which money market primary dealers exerted market power and did not fulfill their role as liquidity conduits (Gale and Yorulmazer, 2013; Acharya et al., 2012,). Thus, identifying key players in the interbank funds market is important because their behavior contributes to determine the most effective set of policy instruments to achieve an efficient interest rate transmission. For instance, as suggested in Acharya et al. (2012), the presence of liquidity abundant financial institutions with market power could support central bank's virtuous role in the efficiency and stability of the interbank market as credible provider of liquidity to a broad spectrum of financial institutions. Also, characterizing the actual topology of the interbank funds network is essential for policymakers because of the relation between its structure and its resilience, robustness, contagion, and efficiency (see, Memmel and Sachs (2013)). In our context, the existence of super-spreaders that provide efficient liquidity shortcuts between financial institutions may alleviate the inefficiencies resulting from the under-provision of liquidity cross-insurance in interbank markets (see Castiglionesi and Wagner (2013)).

This paper proposes an alternative approach to the analysis of the interbank funds market and its role for monetary policy transmission and financial stability. The suggested approach consists of using network analysis and an information retrieval algorithm for studying the connective and hierarchical structure of the Colombian interbank funds market. As suggested by Georg and Poschmann (2010), our approach includes central bank's monetary policy

transactions (i.e. open market operations via repos) in the interbank funds network. Hence, based on a unique dataset, our approach enhances the scope of the traditional network analysis on interbank data. We model interbank market participants linkages and identify how the liquidity provided by the central bank is allocated throughout the interbank market. In particular, we propose a model to identify the most important super-spreaders of the central banks liquidity in the interbank market. We employ several centrality measures as an alternative method to gauge lending relationships in the interbank market following recent approaches in the literature (Craig, et al. 2015).

Our main findings come in the form of the identification of an inhomogeneous and hierarchical connective (core-periphery) structure, in which a few financial institutions fulfill the role of *super-spreaders* of central bank's liquidity within the interbank funds market. We find that those financial institutions have higher *authority centrality* and *hub centrality*, which correspond to their simultaneous importance as global borrowers and lenders, respectively. The main results concur with those of Inaoka et al. (2004), Soramäki et al. (2007), Fricke and Lux (2014), in't Veld and van Lelyveld (2014) and Craig and von Peter (2014) for the Japanese, U.S., Italian, Dutch and German interbank funds markets, respectively. Hence, we find further evidence against traditional assumptions of homogeneity in interbank direct contagion models (à la Allen and Gale, 2000), whereas the similarities across different interbank funds markets' topology support what Fricke and Lux (2014) allege *might be classified as a new "stylized fact" of modern interbank networks*.

Our research work contributes with new tools to examine and understand the structure and dynamics of interbank funds' networks. The resulting insights are important for the implementation of monetary policy and safeguarding financial stability. For instance, testing that the probability of being a super-spreader in the Colombian case is determined by financial institutions' size further supports some of the most salient findings of interbank relationships literature, as those reported in Cocco et al. (2009), Afonso et al. (2013), Fecht et al. (2011). That is, lending relationships are motivated by too-big-to-fail implicit guarantees. Thus, the larger the bank is, the more interconnected and central it is in the interbank network.

This paper is organized in five sections. The second presents the review of existing related literature. The third section introduces the methodological approach, and presents the dataset and its main topological features from the network analysis perspective. The fourth section

presents the main results. The fifth presents a probit model that explores the determinants of the probability of being a super-spreader in the Colombian interbank funds market, and the sixth section concludes.

2. Literature review

The recent GFC evidenced a significant reduction in the intermediation of funds in the interbank market in most industrialized economies. In the case of the U.S., the fragile liquidity conditions forced the Federal Reserve (Fed) into a rapid reduction of its policy rate, and to implement several unconventional measures to bring liquidity directly to the money market primary dealers (i.e. the group of financial institutions that help the Fed implement monetary policy) in order to assure the intermediation of funds among financial institutions. However, instead of serving as liquidity conduits, primary dealers avoided counterparty risk and hoarded, thus aggravating the adverse liquidity conditions (Gale and Yorulmazer, 2013; Afonso et al., 2011).¹ Accordingly, the Fed had to implement additional measures to grant liquidity to other participants of the interbank funds market and to participants of other markets as well (see Fleming (2012); Campbell et al. (2011); Christensen et al. (2009); Duygan et al. (2013)). A similar strategy was implemented by most central banks from industrialized economies. In spite of the liquidity facilities partially alleviated tensions in the financial markets evidence suggests that the interbank market is extremely sensible to liquidity shocks.

One of the main lessons from the GFC is that policy makers have to properly identify the role of the key players in the interbank funds markets. These financial institutions may be considered the driving forces behind the supply and demand for funds in the interbank market, i.e. the liquidity super-spreaders. However, not only super-spreaders may be regarded as those contributing to liquidity transmission the most, but also as those that may distort the distribution of central banks' liquidity the greatest, as was the case of primary dealers in the U.S. interbank funds market, or of credit institutions in the Colombian money

¹ Avoiding counterparty risk and hoarding are unrelated (Gale and Yorulmazer, 2013). In the first case not supplying liquidity to other financial institutions follows concerns on the credit quality of its counterparties, whereas hoarding is due to concerns on its own access to liquidity in the future.

market in 2002². As documented by Acharya et al. (2012), the GFC provides evidence on how banks with excess liquidity in the interbank markets (i.e. *surplus banks*) exerted their market power by rationing liquidity to financial institutions in need of liquidity.³ This underscores the importance of identifying super-spreaders because of their role for financial stability (drivers of contagion risk) and for monetary policy transmission (conduits of central bank money).

Several studies on the topology of interbank funds market networks had been conducted, mainly to identify their properties, such as Inaoka et al. (2004) for Japan (BoJ-NET); Bech and Atalay (2010) and Soramäki et al. (2007) for the U.S. (Fedwire); Boss et al. (2004) for Austria; in't Veld and van Lelyveld (2014) and Pröpper et al. (2008) for the Netherlands; Craig and von Peter (2014) for Germany; Fricke and Lux (2014) for Italy; Cajueiro and Tabak (2008) and Tabak et al. (2013) for Brazil; and Martínez-Jaramillo et al. (2012) for Mexico.⁴ Some of these studies also implement network metrics (e.g. centrality) for analytical purposes related to financial stability and contagion. Only Boss et al. (2004) includes the central bank as a participant in the interbank funds' network, but does not address its particular role. Similarly, Craig, et al. (2015) find that when the network position of the bank is taken into account, central lenders in the money market bid more aggressively in the central bank' auctions. They match the data from the ECB repo auctions with the interbank market operations, but they do not incorporate how the liquidity obtained from the central bank is allocated in the interbank network.

² The Central Bank of Colombia faced a similar stance back in 2002. By mid-2002 a regional market crisis triggered by political stress in Brazil led to the disruption of external credit lines and to a sudden stop that weakened the liquidity position of financial institutions, particularly that of brokerage firms (Vargas and Varela, 2008). These financial institutions were confronted with local credit institutions' reluctance to supply liquidity amidst volatile and uncertain market conditions; as was the case during the GFC, by mid-2002 Colombian credit institutions (i.e. banking firms) with access to central bank's liquidity feared counterparty risk and hoarded. Under these circumstances, the Central Bank decided to move up its standing purchases of local sovereign securities (i.e. TES – Títulos de Tesorería) on the secondary market and to authorize brokerage firms and investment funds to conduct temporary expansion operations with the central bank (BDBR, 2003). Thus, after August 2002 credit institutions, brokerage firms and trust companies have been allowed to access central bank's temporary monetary expansion operations (e.g. open market operations via repos) in the Colombian financial market.

³ Acharya et al. (2012) document how the market power of J.P. Morgan may have resulted in the liquidity rationing that affected non-depository institutions as Bear Sterns amid the GFC. Likewise, Acharya et al. also report that liquidity rationing by super-spreaders may have occurred in several episodes before the GFC, such as the collapse of Long-Term Capital Management in 1998 and of Amaranth Advisors in 2006.

⁴ There are few studies worth mentioning in the Colombian case. Cardozo et al. (2011) and González et al. (2013) describe the functioning of the local money market. Estrada and Morales (2008) and Capera-Romero et al. (2013) study the link between the local interbank funds market structure and financial stability; however, both studies' quantitative and analytical results are limited by their choice of datasets.

In order to identify the topology of the Colombian interbank funds network, our model implements standard network analysis' metrics on a network resulting from merging the Colombian interbank funds market and the central bank's open market operations (i.e. repos). Afterwards, we introduce an information retrieval algorithm to estimate *authority centrality* and *hub centrality* (Kleinberg, 1998), and to identify interbank funds market's super-spreaders. Under our analytical framework a financial institution may be considered a super-spreader for central bank's liquidity if it simultaneously excels at distributing liquidity to other participants (i.e. it is a good hub) and it excels at receiving liquidity from good hubs (i.e. it is a good authority), with the central bank being among the best hubs. To the best of our knowledge, implementing an information retrieval algorithm for identifying super-spreaders in an interbank network that comprises central bank's liquidity provision has not been documented in related literature.

The closest research work is that of Craig and von Peter (2014), Fricke and Lux (2014) and in't Veld and van Lelyveld (2014), who document the existence of core-periphery structures in the German, Italian and Dutch interbank funds markets, respectively. Such tiered hierarchical structure not only concurs with our results, but also verifies the importance of a limited number of financial institutions for the transmission of liquidity within the money market; in this sense, the so-called *top-tier* or *money center banks* of Craig and von Peter (2014) are analogous to our liquidity super-spreaders. However, because their main objective is different from ours, none of those papers include the direct liquidity provision by the central bank in their models, nor do they implement network analysis metrics and an information retrieval algorithm to pinpoint liquidity super-spreaders. Therefore, our work makes a contribution to the identification of central bank's liquidity super-spreaders in interbank funds.

Identifying central bank's money super-spreaders is not only critical for the implementation of monetary policy, but it also coincides with the *robust-yet-fragile* characterization of financial networks by Haldane (2009). This characterization poses major challenges from the financial stability perspective, including the revision of traditional interbank contagion models of Allen and Gale (2000) and of most interbank direct contagion models that followed (e.g. Cifuentes et al. (2005); Gai and Kapadia (2010); Battiston et al. (2012)).

Our results concur with recent literature on the inhomogeneous and core-periphery features of interbank funds networks, and further support that these are stylized facts of interbank funds markets, as claimed by Fricke and Lux (2014). Moreover, an overlooked feature

common to the U.S., Austrian, Dutch and Colombian interbank funds market is revealed: they are *ultra-small* networks in the sense of Cohen and Havlin (2003). This feature is consistent with the existence of a core that provides an efficient short-cut for most peripheral participants in the network, and points out that the structure of these interbank funds networks favors an efficient spread of liquidity, but also of contagion effects.

As tested by Craig and von Peter (2014) for the German interbank market, the probability of being a super-spreader in the Colombian case is determined by financial institutions' size. This result is robust to other samples, and overlap with alternative measures of importance (i.e. centrality) within the interbank funds network. Accordingly, concurrent with literature on lending relationships in interbank markets (Cocco et al. (2009); Afonso et al. (2013)), size may be the main factor behind the interbank funds connective and hierarchical architecture. In this sense, we provide evidence that financial institutions do not connect to each other randomly, but they interact based on a size-related preferential attachment process, presumably driven by too-big-to-fail implicit subsidies or market power.

3. Methodological approach

Three methodological steps are necessary for assessing financial institutions' central bank liquidity spreading capabilities in the local interbank funds market. First, the corresponding network merging interbank funds and monetary policy transactions has to be built from available data. Second, network analysis' basic statistics have to be estimated and interpreted. Third, appropriate metrics for assessing the spreading capabilities of financial institutions have to be chosen. These three steps are introduced next.

3.1. The interbank funds and central bank's repo network

Data from the local large-value payment system (CUD – *Cuentas de Depósito*) was used to filter two types of transactions: interbank funds and central bank's repos. In the Colombian case the interbank funds market is not limited to credit institutions. As defined by local regulation, it corresponds to funds *provided (acquired) by a financial institution to (from) other financial institution without any agreement to transfer investments or credit portfolios*; this is, the interbank funds market consists of all non-collateralized borrowing/lending between all types of financial institutions.

The interbank funds market is the second contributor to the exchange of liquidity between financial institutions in the Colombian money market. As of 2013, the interbank funds market represents about 15.4% of financial institutions' exchange of liquidity, below sell/buy backs on sovereign local securities (84.4%), but above repos between financial institutions (0.2%).⁵ Despite the fact that the use of sell/buy backs between financial institutions exceeds that of the interbank funds market, analyzing the former for monetary purposes may be inconvenient because its interest rate may be affected by the presence of securities-demanding financial institutions (instead of cash-demanding), and by the absence of mobility restrictions on collateral (Cardozo et al., 2011). Hence, as the interbank funds market is the focus of central bank's implementation of monetary policy (Allen et al., 2009), it is also the focus of our analysis.

Central bank's repos correspond to the liquidity granted to financial institutions on behalf of monetary policy considerations by means of standard open market operations, in which the eligible collateral is mainly local sovereign securities. Access to liquidity by means of central bank's repos is open to different types of financial institutions (i.e. banking and non-banking), but is limited to those that fulfill some financial and legal prerequisites. For instance, as of December 2013, 87 financial institutions were eligible for taking part in central bank's repo auctions: 42 credit institutions (CIs), 20 investment funds (IFs), 18 brokerage firms (BKs), 4 pension funds (PFs) and 3 other financial institutions (Xs). As of 2013, the value of Colombian central bank's repo facilities was about six times that of interbank funds transactions.

Merging the interbank funds market and the central bank's repos into a single network follows several reasons. First, by construction, the central bank is the most important participant of the interbank funds market, in which its intervention determines the efficient allocation of money among financial institutions, as underscored by Allen et al. (2009) and Freixas et al. (2011). Second, as in Acharya et al. (2012), the liquidity provision by the central bank is an important factor that may improve the private allocation of liquidity among banks in presence of frictions in the interbank market (i.e. market power by surplus banks). Third, merging both networks allows for comprehensively assessing how central bank's liquidity spreads across financial institutions in the interbank funds market; therefore, as in Georg and

⁵ Only sell/buy backs and repos with sovereign local securities as collateral are considered. Sovereign local securities acting as collaterals for borrowing between financial institutions in the money market usually account for about 80% of the total; if repos with the central bank are included, sovereign local securities represent about 90% of all collateralized liquidity sources.

Poschmann (2010; p.2), *a realistic model of interbank markets has to take the central bank into account*. Fourth, as the access to central bank's repos is open to all types of financial institutions, identifying which institutions effectively access the central bank's open market operations facilities and excel as distributors of liquidity may provide useful information for designing liquidity facilities and implementing monetary policy.

Accordingly, based on data from January 2 to December 17, 2013, Figure 1 displays the actual network resulting from merging the interbank funds market and the central bank's repo facilities.⁶ The direction of the arrow or arc corresponds to the direction of the funds transfer (i.e. towards the borrower), whereas its width represents its monetary value. Only the original transaction (i.e. from the lender to the borrower) is considered; transactions consisting of borrowers paying back for interbank or repo funds are omitted, as are intraday repos.

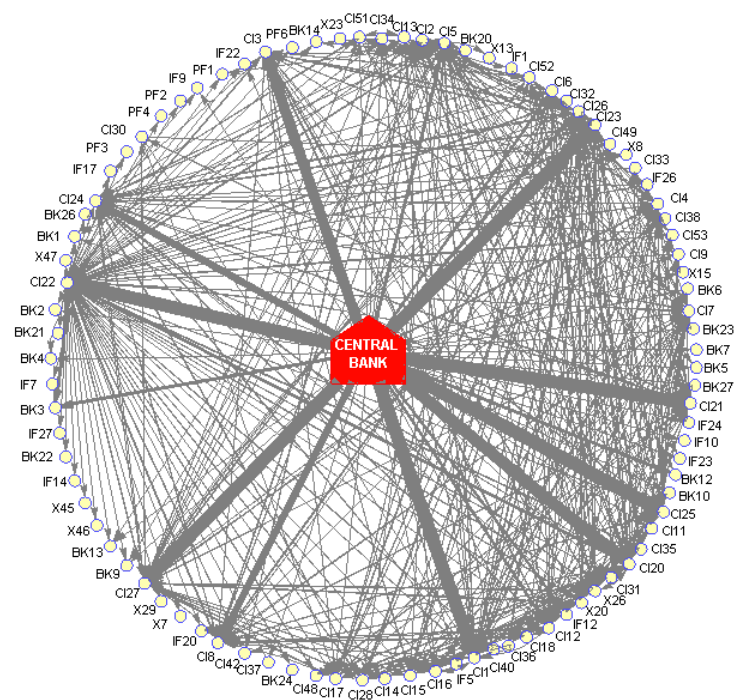


Figure 1. The interbank funds and central bank's repo network. The direction of the arrow corresponds to the direction of the funds transfer (i.e. towards the borrower), whereas its width represents its monetary value. Credit institution (CI); brokerage firm (BK); investment fund (IF); pension fund (PF); other financial institution (X).

⁶ The database was extracted from the large-value payment system (CUD) by means of filtering the corresponding transaction codes; the Colombian Central Bank (i.e. the owner and operator of CUD) assigns transaction codes, and financial institutions and financial infrastructures are obliged to use them to report their transactions.

Some salient features of Figure 1 are worth mentioning. First, due to the open (i.e. non-tiered) access to central bank's liquidity, all types of financial institutions are connected to the central bank via repos. Second, the widest links correspond to funds from the central bank to some credit institutions (e.g. CI22, CI21, CI20, CI1, CI8, CI27, CI3, CI23), which corresponds to the role of the central bank as liquidity provider within 2013's expansionary monetary policy framework. Third, there is a noticeable concentration of interbank links in credit institutions receiving funds from the central bank; the estimated correlation coefficient (0.75) provides evidence of the linear dependence between the liquidity granted by the central bank via repos to financial institutions and their number of links. Fourth, most weakly connected institutions correspond to non-credit institutions.

3.2. Network analysis

A network, or graph, represents patterns of connections between the parts of a system. The most common representation of a network is the *adjacency matrix*. Let n represent the number of vertexes or participants, the adjacency matrix A is a square matrix of dimensions $n \times n$ with elements A_{ij} such that

$$A_{ij} = \begin{cases} 1 & \text{if there is an edge between vertexes } i \text{ and } j, \\ 0 & \text{otherwise.} \end{cases} \quad (1)$$

A network defined by the adjacency matrix in (1) is referred as an undirected graph, where the existence of the (i, j) edge makes both vertexes i and j adjacent or connected, and where the direction of the link or edge is unimportant. However, the assumption of a reciprocal relation between vertexes is inconvenient for some networks. Thus, the adjacency matrix of a directed network or *digraph* differs from the undirected case, with elements A_{ij} being referred as directed edges or arcs, such that

$$A_{ij} = \begin{cases} 1 & \text{if there is an edge from } i \text{ to } j, \\ 0 & \text{otherwise.} \end{cases} \quad (2)$$

It may be useful to assign real numbers to the edges. These numbers may represent distance, frequency or value, in what is called a weighted network and its corresponding weighted adjacency matrix (W_{ij}). For a financial network, the weights could be the monetary value of the transaction or of the exposure.

Regarding the characteristics of the system and its elements, a set of concepts is commonly used. The simplest concept is the vertex *degree* (k_i), which corresponds to the number of edges connected to it. In directed graphs, where the adjacency matrix is non-symmetrical, *in degree* (k_i^{in}) and *out degree* (k_i^{out}) quantifies the number of incoming and outgoing edges, respectively (3).

$$k_i^{in} = \sum_{j=1}^n A_{ji} \qquad k_i^{out} = \sum_{j=1}^n A_{ij} \qquad (3)$$

In the weighted graph case the degree may be informative, yet inadequate for analyzing the network. *Strength* (s_i) measures the total weight of connections for a given vertex, which provides an assessment of the intensity of the interaction between participants. Akin to degree, in case of a directed graph *in strength* (s_i^{in}) and *out strength* (s_i^{out}) sum the weight of incoming and outgoing edges, respectively (4).

$$s_i^{in} = \sum_{j=1}^n W_{ji} \qquad s_i^{out} = \sum_{j=1}^n W_{ij} \qquad (4)$$

Some metrics enable us to determine the connective pattern of the graph. The simplest metric for approximating the connective pattern is *density* (d), which measures the cohesion of the network. The *density* of a graph with no self-edges is the ratio of the number of actual edges (m) to the maximum possible number of edges (5).

$$d = \frac{m}{n(n-1)} \qquad (5)$$

By construction, density is restricted to the $0 < d \leq 1$ range. Networks are commonly labelled as sparse when the density is much smaller than the upper limit ($d \ll 1$), and as dense when the density approximates the upper limit ($d \cong 1$). The term *complete network* is used when $d = 1$.

An informative alternative measure for density is the degree probability distribution (\mathcal{P}_k). This distribution provides a natural summary of the connectivity in the graph (Kolaczyk, 2009). Akin to density, the first moment of the distribution of degree (μ_k) measures the cohesion of the network, and is usually restricted to the $0 < \mu_k < n - 1$ range. A sparse graph has an average degree that is much smaller than the size of the graph ($\mu_k \ll n - 1$).

Most real-world networks display right-skewed distributions, in which the majority of vertexes are of very low degree, and few vertexes are of very high degree, hence the network is inhomogeneous. Such right-skewness of degree distributions of real-world networks has been documented to approximate a power-law distribution (Barabási and Albert, 1999). In traditional random networks, in contrast, all vertexes have approximately the same number of edges.⁷

The power-law (or Pareto-law) distribution suggests that the probability of observing a vertex with k edges obeys the potential functional form in (6), where z is an arbitrary constant, and γ is known as the *exponent* of the power-law.

$$\mathcal{P}_k \propto z k^{-\gamma} \quad (6)$$

Besides degree distributions approximating a power-law, other features have been identified as characteristic of real-world networks: (i) low mean geodesic distances; (ii) high clustering coefficients; and (iii) significant degree correlation, which we explain below.

Let g_{ij} be the *geodesic distance* (i.e. the shortest path in terms of number of edges) from vertex i to j . The mean geodesic distance for vertex i (ℓ_i) corresponds to the mean of g_{ij} , averaged over all reachable vertexes j in the network (Newman, 2010), as in (7). Respectively, the mean geodesic distance or average path length of a network (i.e. for all pairs of vertexes) is denoted as ℓ (without the subscript), and corresponds to the mean of ℓ_i over all vertexes. Consequently, the mean geodesic distance (ℓ) reflects the global structure; it measures how big the network is, it depends on the way the entire network is connected, and cannot be inferred from any local measurement (Strogatz, 2003).

$$\ell_i = \frac{1}{(n-1)} \sum_{j(\neq i)} g_{ij} \quad \ell = \frac{1}{n} \sum_i \ell_i \quad (7)$$

The mean geodesic distance (ℓ) of random or Poisson networks is small, and increases slowly with the size of the network; therefore, as stressed by Albert and Barabási (2002), random graphs are small-world because in spite of their often large size, in most networks there is

⁷ Random networks correspond to those originally studied by Erdős and Rényi (1960), in which connections are homogeneously distributed between participants due to the assumption of exponentially decaying tail processes for the distribution of links –such as the Poisson distribution. This type of network, also labeled as “random” or “Poisson”, was –explicitly or implicitly– the main assumption of most literature on networks before the seminal work of Barabási and Albert (1999) on scale-free networks.

relatively a short path between any two vertexes. For random networks: $\ell \sim \ln n$ (Newman et al., 2006). This slow logarithmic increase with the size of the network coincides with the small-world effect (i.e. short average path lengths).

However, the mean geodesic distance for scale-free networks is smaller than $\ell \sim \ln n$. As reported by Cohen and Havlin (2003), scale-free networks with $2 < \gamma < 3$ tend to have a mean geodesic distance that behaves as $\ell \sim \ln \ln n$, whereas networks with $\gamma = 3$ yield $\ell \sim \ln n / (\ln \ln n)$, and $\ell \sim \ln n$ when $\gamma > 3$. For that reason, Cohen and Havlin (2003) state that scale-free networks can be regarded as a generalization of random networks with respect to the mean average geodesic distance, in which scale-free networks with $2 < \gamma < 3$ are “ultra-small”.

Network analysis’ basic statistics estimated for the interbank funds and central bank’s repo network are presented in Table 1. Evidence advocates that the network is (i) sparse, with low density resulting from the number of observed links being much smaller than the potential number of links, and with an average degree (i.e. mean of links per institution) much smaller than the number of participants; (ii) ultra-small in the sense of Cohen and Havlin (2003), in which the average minimal number of links required to connect any two financial institutions (i.e. the mean geodesic distance) is particularly low (i.e. ~ 2) with respect to the number of participants; (iii) inhomogeneous, in which the dispersion, asymmetry, kurtosis and the order of the power-law exponent for the distribution of links and their monetary values suggest the presence of a few financial institutions that are heavily connected and large contributors to the system, whereas most institutions are weakly connected and minor contributors, with the distribution of degree and strength presumably approximating a scale-free distribution;⁸ (v) *assortative mixing by degree*, which means that heavily (weakly) connected financial institutions tend to be connected with other heavily (weakly) connected, especially for the in-degree case.

⁸ The estimation of the power-law exponent was based on the maximum likelihood method proposed by Clauset et al. (2009); this method is preferred to the traditional ordinary least-squares due to documented issues regarding the latter (as in Clauset et al., 2009, Stumpf and Porter, 2012). Despite some of the estimated power-law exponents do not make a strong case based on the goodness-of-fit tests of Clauset et al. (2009), the level of the exponent provides enough evidence of the alleged inhomogeneity in the distribution of degree and strength. Moreover, as the power-law distribution of links is an asymptotic property, a strict match between observed and expected theoretical properties for determining the scale-free properties of non-large networks may be impractical.

Table 1		
Standard statistics for the interbank funds and central bank's repo network		
Statistic	Including the central bank	Excluding the central bank
Participants	92	91
Density	0.07 ^a	0.07
Mean geodesic distance	2.04	2.05
Degree	(In Out)	(In Out)
<i>Mean</i>	6.62 6.62	6.16 6.16
<i>Standard deviation</i>	8.35 10.68	8.17 10.00
<i>Skewness</i>	1.59 2.55	1.59 2.64
<i>Kurtosis</i>	4.78 11.33	4.81 13.11
<i>Power-law exponent</i>	1.60 3.50 ^b	1.60 1.71
<i>Assortativity index</i>	0.54 0.06	0.57 0.15
Strength	(In Out)	(In Out)
<i>Mean</i>	1.09 1.09	1.10 1.10
<i>Standard deviation</i>	3.35 8.49	3.16 3.02
<i>Skewness</i>	5.37 9.37	6.40 4.29
<i>Kurtosis</i>	37.24 89.24	51.32 24.99
<i>Power-law exponent</i>	1.43 2.00 ^b	3.14 ^b 1.41
<i>Assortativity index</i>	0.04 -0.05	0.05 -0.01

This table shows that the interbank funds and central bank's repo network is an approximate scale-free network, akin to other social networks documented in literature, and it resembles a core-periphery structure. ^a The calculation of density is adjusted for the exclusion of financial institutions' payback for the repo. ^b Based on Clauset et al. (2009) goodness-of-fit tests, there is a strong case for a power-law distribution with the estimated exponent.

Altogether, these features concur with the scale-free and assortative mixing by degree connective structure of social networks reported by Newman (2010), and suggest the presence of a structure similar to a core-periphery within the network under analysis. Moreover, as the interbank funds network is ultra-small in the sense of Cohen and Havlin (2003), with participants being one financial institution away from the others, the process of liquidity spreading within the interbank funds network is highly efficient; likewise, contagion spreads within the network with ease. These main features are robust to the exclusion of the central bank.

A remarkable but overlooked feature in Table 1 is worth noting. A mean geodesic distance around 2 not only agrees with ultra-small networks (Cohen and Havlin, 2003), but also suggests that the bulk of financial institutions require about two links (i.e. circa one financial institution in-between) to connect to any other financial institution in the interbank funds network, meaning that the core provides an efficient short-cut for most peripheral participants in the network; again, the spreading capabilities of the network are particularly

high. Interestingly, mean geodesic distances reported by Boss et al. (2004), Soramäki et al. (2007), Bech and Atalay (2010), and Pröpper et al. (2008), for the Austrian, U.S. and Dutch interbank funds networks are about 2, consistent with ultra-small networks and with the role of a core providing an effective short-cut for the network; likewise, mean geodesic distances reported by León and Berndsen (2014) for the Colombian large-value payment system (CUD) and the main local sovereign securities settlement system (DCV – *Depósito Central de Valores*) are also about 2.

All in all, these findings concur with those of Craig and von Peter (2014) about the presence of tiering in the interbank funds market in the German banking system, and with the corresponding *money center banks*. Moreover, as also highlighted by Craig and von Peter (2014), these features verify that the connective structure of financial networks departs from traditional assumptions of homogeneity and representative agents (as in Allen and Gale (2000); Freixas et al. (2000); Cifuentes et al. (2005); Gai and Kapadia (2010)), and further supports the need to achieve the main goal of this paper: identifying which financial institutions are particularly relevant for the network.

3.3. Identifying super-spreaders in financial networks

Whenever financial networks' observed connectedness structure is inhomogeneous the underlying system's fragility issue arises. In those networks the extraction or failure of a participant will have significantly different outcomes depending on how the participant is selected. When randomly selected, the effect will be negligible, and the network may withstand the removal of several randomly selected participants without significant structural changes. However, if selected because of their high connectivity, extracting a small number of participants may significantly affect the network's structure. In this sense, a rising amount of financial literature is encouraging the usage of network metrics of importance (e.g. centrality) for identifying super-spreaders (Markose et al. (2012); Markose (2012); León et al. (2012); Haldane and May (2011); Haldane (2009)).

Most literature on financial super-spreaders seeks to identify those institutions that may lead contagion effects due to their network connectivity, *high-infection individuals* (Haldane, 2009), or those that *dominate in terms of network centrality and connectivity* (Markose et al., 2012). Despite the traditional negative connotation of super-spreaders in financial networks, in the

present case the super-spreader financial institution is considered a good conduit for monetary policy as well.

There are many approaches for assessing the importance of individuals or institutions within a network. However, centrality is the most common concept, with many definitions and measures available. The simplest measures are related to local metrics of centrality, such as degree (i.e. number of links, k_i) or strength (i.e. weight of links, s_i), but they fall short to take into account the global properties of the network; this is, the centrality of the counterparties is not taken into account as a source of centrality. Moreover, they do not capture the in-between or intermediation role of vertexes.

An alternative to degree and strength centrality is betweenness centrality. It measures the extent to which a vertex lies on paths of other vertexes (Newman, 2010). It is based on the role of the i -vertex in the geodesic (i.e. the shortest) path between two other (p and q) vertexes (\mathcal{G}_{pq}). Accordingly, let $u_{pq,i}$ be the number of geodesic paths from p to q that pass through vertex i , and v_{pq} the total number of geodesic paths from p to q , the betweenness centrality of vertex i (\mathcal{C}_i) is

$$\mathcal{C}_i = \sum_{pq} \frac{u_{pq,i}}{v_{pq}} \quad (8)$$

In the case at hand, betweenness centrality is appealing. A central intermediary in the interbank funds market should fulfill an in-between role for the network: it should stand in the interbank funds' path of other financial institutions. Yet, as it is a path-dependent centrality measure, it does not consider linkages' intensity or value, and it that does not consider the centrality of adjacent nodes as a source of centrality.

The simplest global and non-path-based measure of centrality is eigenvector centrality, whereby the centrality of a vertex is proportional to the sum of the centrality of its adjacent vertexes; accordingly, the centrality of a vertex is the weighted sum of centrality at all possible order adjacencies. Hence, in this case centrality arises from (i) being connected to many vertexes; (ii) being connected to central vertexes; (iii) or both.⁹ Alternatively, as put forward

⁹ For instance, Markose et al. (2012) use eigenvector centrality to determine the most dominant financial institutions in the U.S. credit default swap market, and to design a super-spreader tax that mitigates potential socialized losses.

by Soramäki and Cook (2012), eigenvector centrality may be thought of as the proportion of time spent visiting each participant in an infinite random walk through the network.

Eigenvector centrality is based on the *spectral decomposition* of a matrix. Let Ω be an adjacency matrix (weighted or non-weighted), Λ a diagonal matrix containing the eigenvalues of Ω , and Γ an orthogonal matrix satisfying $\Gamma\Gamma' = \Gamma\Gamma = I_n$, whose columns are eigenvectors of Ω , such that

$$\Omega = \Gamma\Lambda\Gamma' \quad (9)$$

If the diagonal matrix of eigenvalues (Λ) is ordered so that $\lambda_1 \geq \lambda_2 \cdots \lambda_n$, the first column in Γ corresponds to the principal eigenvector of Ω . The principal eigenvector (Γ_1) may be considered as the leading vector of the system, the one that is able to explain the most of the underlying system, in which the positive n -scaled scores corresponding to each element may be considered as their weights within an index.

Because the largest eigenvalue and its corresponding eigenvector provide the highest accuracy (i.e. explanatory power) for reproducing the original matrix and capturing the main features of networks (Straffin, 1980), Bonacich (1972) envisaged Γ_1 as a global measure of popularity or centrality within a social network.

However, eigenvector centrality has some drawbacks. As stated by Bonacich (1972), eigenvector centrality works for symmetric structures only (i.e. undirected graphs); however, it is possible to work with the right (or left) eigenvector (as in Markose et al., 2012), but this may entail some information loss. Yet, the most severe inconvenience from estimating eigenvector centrality on asymmetric matrices arises from vertexes with only outgoing or incoming edges, which will always result in zero eigenvector centrality, and may cause some other non-strongly connected vertexes to have zero eigenvector centrality as well (Newman, 2010). In the case of acyclic graphs, such as financial market infrastructures' networks (León and Pérez, 2014), this may turn eigenvector centrality useless; this is also our case because the central bank has no incoming links, and because some peripheral financial institutions are weakly connected.

Among some alternatives to surmount the drawbacks of eigenvector centrality (e.g. PageRank, Katz centrality), the HITS (Hypertext Induced Topic Search) information retrieval algorithm by Kleinberg (1998) is convenient for several reasons. There are four main advantages in our

case: (i) unlike eigenvector centrality, it is designed for directed networks, in which the adjacency matrix may be non-symmetrical; (ii) it provides two separate centrality measures, *authority centrality* and *hub centrality*, which correspond to the eigenvector centrality as recipient and as originator of links, respectively; (iii) when dealing with weakly connected vertexes, it avoids introducing stochastic or arbitrary adjustments (as in PageRank and Katz centrality) that may be undesirable from an analytical point of view, and (iv) because the authority (hub) centrality of each vertex is defined to be proportional to the sum of the hub (authority) centrality of the vertexes that point to it (it points to), the importance of vertexes fulfilling an in-between role for the network tends to be captured.¹⁰

The estimation of authority centrality (a_i) and hub centrality (h_i) results from estimating standard eigenvector centrality (9) on two modified versions of the weighted adjacency matrix, \mathcal{A} and \mathcal{H} (10).

$$\mathcal{A} = \Omega^T \Omega \qquad \mathcal{H} = \Omega \Omega^T \qquad (10)$$

Multiplying the adjacency matrix with a transposed version of itself allows identifying directed (*in* or *out*) second order adjacencies. Regarding \mathcal{A} , multiplying Ω^T with Ω sends weights backwards –against the arrows, towards the pointing node–, whereas multiplying Ω with Ω^T (as in \mathcal{H}) sends scores forwards –with the arrows, towards the pointed-to node (Bjelland et al., 2008). Thus, the HITS algorithm works on a circular thesis: the authority centrality (a_i) of each participant is defined to be proportional to the sum of the hub centrality (h_i) of the participants that point to it, and the hub centrality of each participant is defined to be proportional to the sum of the authority centrality of the participant it points-to.

The circularity of the HITS algorithm is most convenient for identifying super-spreaders of central bank’s liquidity. An institution may be considered a good conduit for central bank’s liquidity if it simultaneously is a good hub (i.e. it excels at distributing liquidity within the interbank funds market) and a good authority (i.e. it excels at receiving liquidity from good hubs, with the central bank being among the best hubs). On the other hand, if an institution is a good authority but a meager hub it may be regarded as a poor conduit for central bank’s

¹⁰ The relevance of the in-between role of a vertex has an inverse relation with the existence of other vertexes providing the same connective role. Thus, a vertex being the sole provider of a connective role will concentrate all the weighted average centrality of the vertexes it connects. Thus, in this sense, the HITS algorithm captures the in-between role of vertexes.

liquidity; likewise, if an institution is a good hub but a modest authority its central bank's liquidity transmission capabilities may be regarded as low.

The eigenvector centrality framework behind the estimation of authority centrality and hub centrality allows both metrics to capture the impact of liquidity on a global scale. Accordingly, all financial institutions that are connected to the central bank and the most important hubs, either directly or indirectly, inherit some degree of authority centrality depending on the intensity of the links to those providers of liquidity. Likewise, all financial institutions that distribute liquidity in the system inherit some degree of hub centrality depending on the intensity of the links to all those receiving liquidity.

In this sense, an institution simultaneously displaying a high score in both authority (a_i) and hub centrality (h_i) is expected to be a dominant participant in the transmission of funds from the central bank to the interbank funds market and within the interbank funds market. Therefore, the liquidity spreading index of an i -financial institution (LSI_i) corresponds to the product of both normalized centrality measures, as in (11). The choice of the product operator is consistent with the aim of identifying institutions that simultaneously are a good hub and a good authority.¹¹

$$LSI_i = \frac{\left(\frac{a_i}{\sum_{i=1}^n a_i} \times \frac{h_i}{\sum_{i=1}^n h_i} \right)}{\sum_{i=1}^n \left(\frac{a_i}{\sum_{i=1}^n a_i} \times \frac{h_i}{\sum_{i=1}^n h_i} \right)} \quad (11)$$

Where, by construction

$$0 \leq LSI_i \leq 1$$

And

$$LSI = \sum_{i=1}^n LSI_i = 1$$

¹¹ Other conjunction operators may be chosen, such as $\min(\cdot)$. Using the average of hub centrality and authority centrality is feasible, but may fail to discard institutions that are good authorities but mediocre hubs, and vice versa.

Since LSI_i is a measure of the contribution of an individual financial institution to the product of all financial institutions' hub and authority centrality, super-spreaders may be defined as those contributing the most to LSI . Super-spreaders are those financial institutions that simultaneously excel as global borrowers and lenders of central bank's money in the interbank funds network. To the best of our knowledge, this is the first attempt to use a global and non-path dependent centrality measure to identify super-spreaders in an interbank network comprising the central bank.

4. Main results

Based on the methodological approach described in the previous section, the liquidity-spreading index (LSI_i) was estimated for the interbank funds and central bank's repo network. This network comprises 28,393 lending transactions from January 2 to December 17, 2013. Figure 2 presents the top-30 financial institutions by their estimated LSI_i .¹²

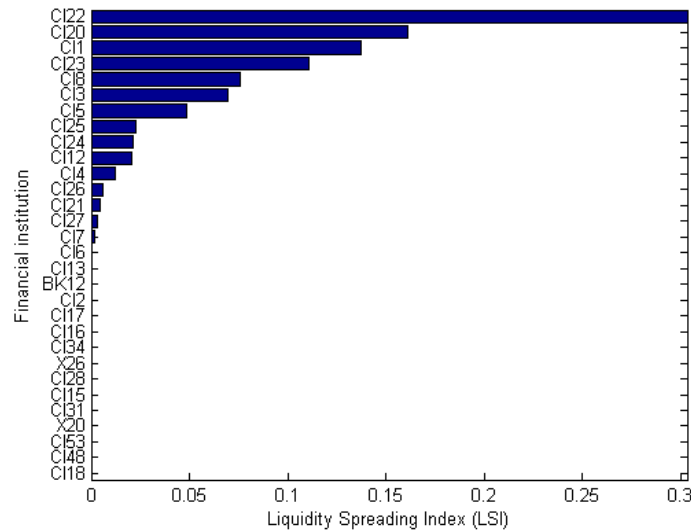


Figure 2. Top-30 financial institutions by estimated LSI_i . Credit institutions (CI) dominate the contribution to LSI . Other types of contributing institutions are brokerage firms (BKs) and other financial institutions (Xs).

¹² The central bank's LSI_i is neither reported, nor analyzed. After estimating LSI_i as in (14) the central bank's score is excluded, and the remaining scores are standardized accordingly. This follows our focus on identifying super-spreader financial institutions different from the central bank. The same procedure applies for other centrality measures here implemented

The first 17 are credit institutions (CIs), which together contribute with 99.98% of *LSI*. The concentration in the top-ranked financial institutions is clear, with the first (CI22) contributing with about 30% of the *LSI*, and the top-five (CI22, CI20, CI1, CI23, CI8) contributing with about 79%. Hence, results suggest that CIs provide the main conduit for central bank's liquidity within the Colombian financial system. As reported in Appendix 1, CIs providing the main conduit for central bank's liquidity is robust to other samples (i.e. 2011 and 2012). Likewise, the most important super-spreaders (e.g. CI22, CI20, CI1, CI23) tend to be stable across samples.

Figure 3 displays a hierarchical visualization of how liquidity spreads from the central bank throughout the interbank funds market. The hierarchies introduced correspond to different levels of contribution to *LSI*. Two levels were chosen for illustrative purposes: the first layer (i.e. the closest to the central bank, in green boxes) corresponds to those eleven financial institutions in the 99th percentile of *LSI*, whereas the second layer corresponds to those eighty whose contribution is about 1% of the *LSI*. The height of the boxes corresponds to the authority centrality (i.e. importance as global borrower, a_i), whereas their width to the hub centrality (i.e. importance as global lender, h_i), with those financial institutions receiving liquidity directly from the central bank (i.e. via repos) appearing with a thicker (red) border; the width of the arrows correspond to the monetary value of the transactions, whereas their direction corresponds to the direction of the funds (i.e. towards the borrower).

Visual inspection of Figure 3 yields some interesting remarks. Regarding the first layer, it is unmistakable that it congregates the biggest (i.e. highest and widest) boxes, which signals their superior liquidity spreading capabilities within the network; in this sense, under the arbitrarily chosen percentiles, the first layer gathers what could be considered as central bank's liquidity super-spreaders: CI22, CI25, CI1, CI24, CI23, CI4, CI12, CI3, CI5, CI8, CI20.

It is also visible that the height (i.e. authority centrality) and width (i.e. hub centrality) of financial institutions in the first layer is dissimilar in cross-section: some boxes (e.g. CI1 and CI23) are squared (i.e. with similar authority and hub centrality), whereas others are vertical (i.e. larger authority centrality, e.g. CI22) or horizontal rectangles (i.e. larger hub centrality, e.g. CI20). Such contrast suggests that super-spreaders are not homogeneous. Moreover, this contrast overlaps with the estimated linear dependence between hub centrality and authority (see Appendix 2), in which correlation is positive, yet not decisively strong (i.e. 0.33).

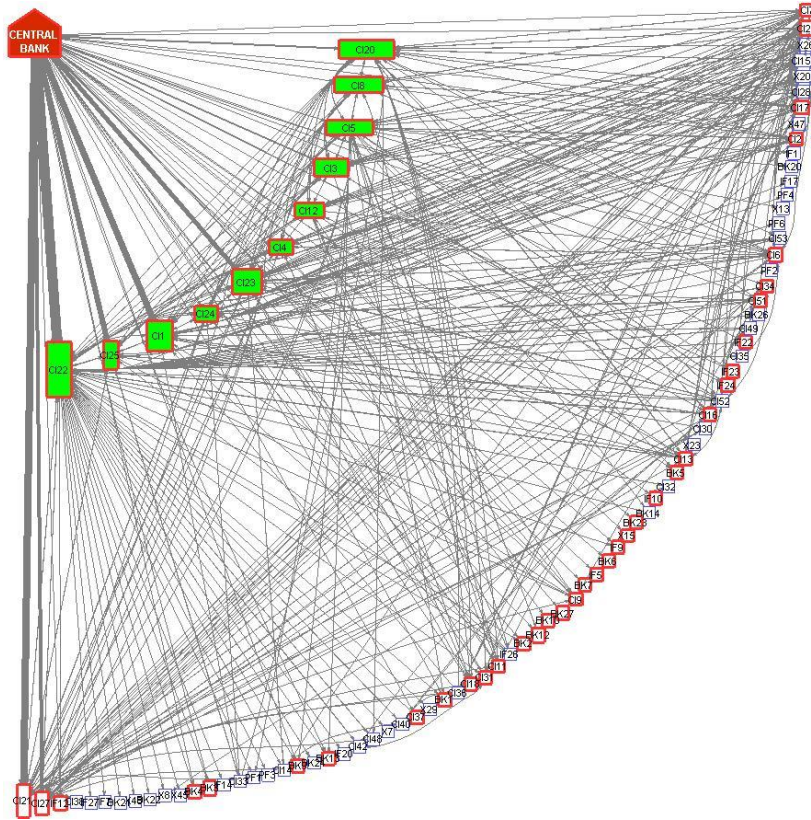


Figure 3. Hierarchical visualization of the interbank funds and central bank's repo network. The height of the boxes corresponds to the authority centrality (a_i), width to the hub centrality (h_i); the first layer of institutions (in green) corresponds to the 99th percentile of the LSI_i ; financial institutions receiving liquidity directly from the central bank are marked with a thicker (red) border; as usual, the width of the arrows corresponds to the monetary value of the transactions, whereas their direction goes towards the borrower. Institutions in the visualization are credit institutions (CIs); brokerage firms (BKs); investment funds (IFs); pension funds (PFs); other financial institutions (Xs).

It is noticeable that the first layer congregates credit institutions (CIs) only, whereas the second displays a mixed composition. Also, financial institutions in the first layer tend to coincide with those that directly receive the most liquidity from the central bank (i.e. by the width of the arrows), and they all have direct linkages to the central bank (i.e. boxes with red borders). However, several financial institutions in the second layer also have direct links to the central bank, with CI21 receiving a particularly large amount of liquidity from the central bank but failing to distribute it within the network (i.e. a high yet narrow box).

Figure 4 displays the graph corresponding to the interbank funds transactions between the eleven institutions in the first layer (i.e. the core) of Figure 3. The diameter of the circles

corresponds to the value of each financial institution's lending within the core network; as usual, the width of the arrows corresponds to the monetary value of the transactions, whereas their direction corresponds to the direction of the funds (i.e. towards the borrower). The sum of transactions' value within the core represents 52.07% of the interbank funds network.

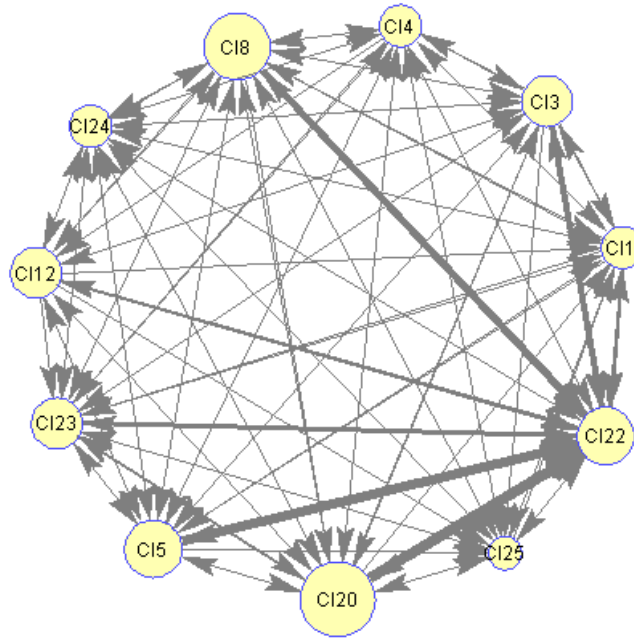


Figure 4. The interbank funds core network. Credit institutions (CIs) here included correspond to those in the first layer of Figure 3. The diameter of the circles corresponds to the value of the lending within the core network; as usual, the width of the arrows corresponds to the monetary value of the transactions, whereas their direction goes towards the borrower.

As expected, the core is a dense graph (i.e. 93.6% of the potential connections is observed), with a mean geodesic distance about 1.06, in which the degree is evenly distributed (i.e. mean degree 9.36; standard deviation about 1.00). Nevertheless, the strength displays inhomogeneity, with the diameter of each financial institution and the width of arrows varying in cross section; for instance, the total lending of CI20 is about 15 times that of CI25, whereas the total borrowing of CI22 is about 177 times that of CI12.

Regarding the periphery, it is evident that most financial institutions in Figure 3 display small boxes (i.e. low authority and hub centrality). This not only concurs with previous evidence of inhomogeneity in the network under analysis, but also with literature on financial networks.

It is also noticeable that many financial institutions in the second layer maintain very few connections with the rest of the network, most of them as borrowers, which suggests that during the period under analysis (i.e. almost a yearlong) they had a limited number of counterparties in the interbank funds market, either by choice or by market constraints. On the other hand, all financial institutions in the first layer appear to be heavily connected to the entire network, as borrowers and lenders, as expected from core financial institutions in a core-periphery structure.

Figure 5 displays the graph corresponding to the interbank funds transactions between the institutions in the second layer of Figure 3 (i.e. the periphery). The sum of transactions' value within the periphery represents 10.66% of the whole interbank funds network, whereas transactions between the core and the periphery represent about 37.27%. Such preference of peripheral financial institutions to maintain relationships with the core overlaps with evidence reported by Cocco et al. (2009), Fricke and Lux (2014) and Craig and von Peter (2014) and Craig et al. (2015).

As expected, the periphery is a sparse graph (i.e. 2.4% of the potential connections is observed), in which degree and strength are unevenly distributed; mean degree is about 1.9, with a standard deviation about 3.5, whereas mean strength is about 1.3% with a 4.0% standard deviation.¹³ Most peripheral institutions (48) have no links with other peripheral institutions during the period under analysis (i.e. about one year), which means that their liquidity sources were restricted to borrowing from core financial institutions or the central bank. The residual, comprised by 32 institutions, are rather well-connected between them, and most of them (30) are credit institutions.

¹³ As is customary to exclude non-reachable (i.e. unconnected) participants from the calculation of the mean geodesic distance, and because most of the financial institutions are non-reachable, the mean geodesic distance of the periphery may not be informative, thus it is not reported.

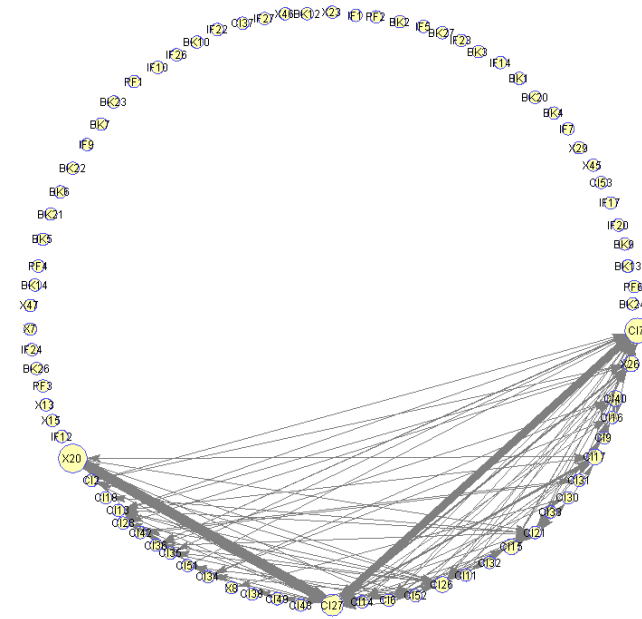


Figure 5. The interbank funds periphery network. Institutions here included correspond to those in the second layer of Figure 3. The diameter of the circles corresponds to the value of the lending within the periphery network; as usual, the width of the arrows corresponds to the monetary value of the transactions, whereas their direction goes towards the borrower. Institutions in the visualization are credit institutions (CIs); brokerage firms (BKs); investment funds (IFs); pension funds (PFs); other institutions (Xs).

5. What makes a super-spreader in the Colombian interbank funds market?

The size of institutions in financial markets is known to be inhomogeneous, with a few that may be regarded as “too-large” and many “too-small”, presumably approximating a power-law distribution (Gabaix et al. (2003); Fiaschi et al. (2013)), even in the Colombian case (León, 2014). Craig and von Peter (2014), Fricke and Lux (2014), in’t Veld and van Lelyveld (2014), and Cajueiro and Tabak (2008) confirm that there is a significant relation between financial institutions’ size and their position in the interbank funds’ hierarchy in the respective German, Italian, Dutch, and Brazilian interbank markets. In these markets large banks tend to be in the core, whereas small banks are found in the periphery. This is consistent with Cocco et al. (2009), who report that size is an important determinant of interbank lending relationships, with smaller banks being less likely to act as intermediaries.

Regarding the Colombian case the relation between size and the role as super-spreader in the interbank funds market is evident. Figure 6 exhibits the double logarithmic scale plot for Colombian financial institutions' assets value, in which the horizontal axis corresponds to the logarithm of assets value, the vertical axis to the logarithm of the cumulative frequency for each asset value, and each circle represents a single financial institution. As also reported by Fiaschi et al. (2013) for the U.S. financial market, such double logarithmic plot exhibits an interesting feature: it is an "interrupted" plot. Such interruption, also reported for the Colombian case (León, 2014), yields two different size regimes with two different distributional forms. It verifies that in the Colombian financial market there are large (i.e. above COP 8.8 Trillion) and small (i.e. below COP 2.5 Trillion) financial institutions, and that they may be pinpointed rather objectively.

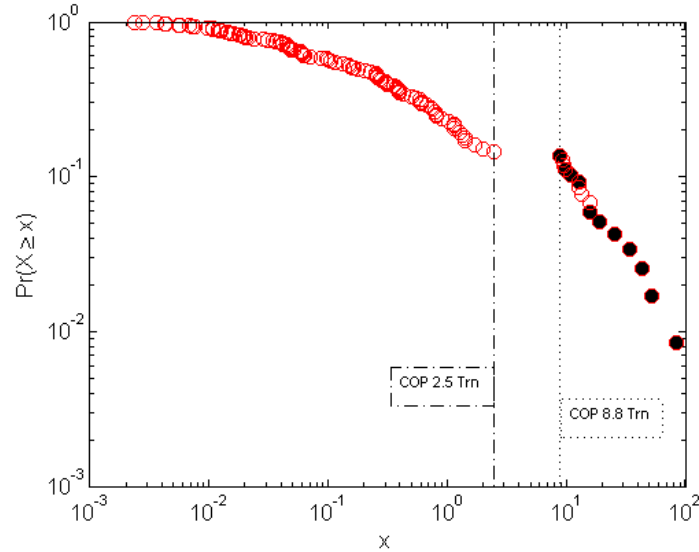


Figure 6. Distribution of Colombian financial institutions' size (double logarithmic scale). There are two different size regimes, in which super-spreaders in Figure 3 (filled circles) correspond to large financial institutions. Size corresponds to the 2013 average asset value reported by the Financial Superintendence of Colombia; filled circles correspond to super-spreaders in Figure 3. Based on León (2014).

Filling (in black) the circles corresponding to the super-spreaders (i.e. financial institutions in the 99th percentile of *LSI*, Figure 3) yields an obvious observation: in the Colombian interbank funds market all super-spreaders pertain to the largest financial institutions regime (i.e. assets above COP 8.8 trillion). The average size of super-spreaders is about 33 times that of other financial institutions; this agrees with evidence reported by Craig and von Peter (2014) for the German interbank funds market (i.e. about 51 times). Therefore, two distinctive

features may determine super-spreading capabilities of financial institutions in the Colombian interbank funds market, namely being a credit institution and being large.

In order to provide further evidence on the characteristics of the financial institutions that may be considered as super-spreaders, we implement a probit regression model on a set of institution-specific variables that are standard in the literature: size, leverage, financial performance, and the concentration of borrowing and lending counterparties. These variables serve as regressors in the probit model, in which the dependent variable (LSI_i) is binary according to financial institution's super-spreader features: $LSI_i = 1$ if it pertains to the 99th percentile (i.e. it is a super-spreader), and $LSI_i = 0$ otherwise.

Regarding the choice of the independent variables, not only size (*size*) is a leading determinant of the position within a core-periphery structure for the German, Italian and Dutch interbank markets, but graphical inspection of Figure 6 also points out the relevance of size in the Colombian case. Leverage (*lev*) corresponds to the traditional debt to assets ratio, which is intended to test whether super-spreaders may be predicted by the capital structure of financial institutions. Financial performance corresponds to the return over assets ratio (*roa*), which is intended to test whether super-spreaders may be predicted by their profitability. Finally, the borrowing concentration (*borr*) and lending concentration (*lend*) correspond to the calculation of the Herfindahl-Hirschman index (HHI) on the contribution of borrowing and lending counterparties for each financial institution, respectively. Including these two variables aims at examining whether concentrating (or diversifying) counterparties may serve to predict super-spreaders.¹⁴

Accordingly, based on the choice of percentile for the dataset under analysis, the probit regression model serves as a test of the significance of the selected institution-centric variables for predicting the membership of the eleven super-spreaders in Figure 3. Let X represent the set of institution-specific variables (i.e. *size*, *lev*, *roa*, *borr*, *lend*); pr denote

¹⁴ Financial institutions' access to central bank's liquidity –an intuitive variable– would predict super-spreaders perfectly; hence, despite its consideration in the probit model makes its estimation unfeasible, it should be considered for analytical purposes. Some institution-centric variables (e.g. equity, return over equity) were discarded due to their lack of significance or redundancy with those presented, whereas others (e.g. non-performing loans) were excluded because they are available for credit institutions only. Initial liquidity balance in central bank's accounts, cash, and proprietary investments, were discarded due to potential multicollinearity with size; the cross-correlation between the three variables is high, and asset size encompasses them all. Likewise, the value of repos with the central bank is also discarded for potential multicollinearity with size.

probability; and Φ the Cumulative Distribution Function of the standard normal distribution, the probit regression model is as in (12).

$$pr(LSI_i = 1 | X) = \Phi(X'\beta) \quad (12)$$

Where

$$LSI_i = \begin{cases} 1 & \text{if } i \text{ is a super-spreader} \\ 0 & \text{otherwise} \end{cases}$$

The independent variables correspond to daily averages during the sample (i.e. January 2 – December 17, 2013). All independent variables are standard scores (i.e. number of standard deviations above the estimated mean). Standard descriptive statistics for the variables are presented in Appendix 3.

However, because the functional form of LSI_i in (11) seeks to filter out those financial institutions that simultaneously display both authority centrality (a_i) and hub centrality (h_i), the same probit regression model is implemented in two alternate models with authority and hub centrality as dependent variables. Using authority centrality and hub centrality as alternative dependent variables helps us to examine if the selected independent variables differ in their explanatory power because of the potentially distinct role of financial institutions as global receivers or distributors of liquidity. Simple local centrality measures, namely degree (i.e. number of links, k_i) and strength (i.e. weight of links, s_i), and betweenness centrality (i.e. role as connector between vertexes, b_i) are also reported for robustness and comparison purposes.

Overall, concurrent with the literature, we expect a strong and positive linear dependence between size and the probability of being a super-spreader. One would expect that the more leveraged a financial institution is, the cheaper its cost of capital, and consequently the cheaper the liquidity it may lend. Therefore, we expect a positive relation between leverage and the probability of being a super-spreader and a good hub, but we do not have a clear expectation on the relation with the probability of being a good authority. Regarding financial performance, as larger banks are reported to be more cost and profit efficient than their smaller peers in the intermediation of funds in the Colombian financial system (Sarmiento and Galán, 2014), we expect a positive and linear dependence between financial performance and the probability of being super-spreader, good hub, and good authority. About the

concentration of borrowing and lending, we expect an inverse relation between concentration of counterparties and the probability of being a super-spreader; on the other hand, the probability of not being a super-spreader is expected to be high for peripheral financial institutions, which have been documented to concentrate their borrowing relationships (see Afonso et al. (2013) and Cocco et al. (2009), who analyze small financial institutions in the periphery of the U.S. and Portuguese interbank markets, respectively).

Regarding alternative centrality measures, we expect financial institutions' degree (k_i), strength (s_i), and betweenness (b_i) to coincide with their LSI_i . As LSI_i is a global measure of centrality that incorporates the number of linked neighbors, the intensity of the linkages at all possible order adjacencies, and the in-between role of vertexes, we expect to observe consistency with degree, strength and betweenness. The linear dependence (i.e. correlation) between the selected dependent variables supports such expectation (see Appendix 2).

Table 2 shows the results of estimating the probit regression model in (15)¹⁵. The overall fit of the probit model is adequate for predicting super-spreaders: the pseudo R-squared is about .74, and the estimated model predicts 93.51% of the observations (96.97% of $LSI_i = 0$ and 75.29% of $LSI_i = 1$). Size is the sole significant determinant of the probability of being a super-spreader. This concurs with Craig and von Peter's (2014) findings of large banks that dominate wholesale activity in money markets (i.e. *money center banks*) in the German interbank market.

As expected, size is the major determinant of the probability of being a super-spreader, a good hub, and a good authority. Likewise, size is the major determinant of the probability of displaying high degree, strength and betweenness. In the case of hub centrality, strength and betweenness, the probability is also determined by borrowing concentration, in which the negative sign denotes that the less concentrated the borrowing counterparties, the more likely is to be a central financial institution in the interbank funds market. Leverage, financial performance, and lending concentration are neither determinants of the probability of being a super-spreader, nor determinants of the probability of being central to the network. These results are robust to other samples (i.e. 2011 and 2012, in Appendix 4). Also, as expected, there is consistency between LSI_i and the alternative dependent variables.

¹⁵ An analogous Ordinary Least Squares cross-section model yielded results consistent with those attained with the probit model here reported.

Table 2						
Probit regression on selected determinants						
Variable ^{a, b}	LSI_i	\mathcal{H}_i	a_i	\mathcal{H}_i^h	s_i	\mathcal{B}_i
Size (size) ^c	2.758 (2.40)**	2.456 (3.16)***	3.848 (3.38)***	168.48 (1.80)*	3.644 (2.34)**	1.585 (2.43)**
Leverage (lev) ^d	1.002 (0.41)	0.322 (0.85)	-0.101 (-0.51)	0.065 (0.31)	-0.233 (-1.34)	0.988 (0.95)
Financial performance (roa) ^e	-0.377 (-0.29)	-0.320 (-1.26)	0.128 (0.77)	0.157 (0.72)	0.005 (0.03)	-0.458 (-0.80)
Borrowing concentration (borr) ^f	0.010 (0.03)	-0.765 (-3.43)***	0.324 (1.44)		-0.392 (-2.09)**	-0.664 (-2.42)**
Lending concentration (lend) ^g	-0.069 (-0.11)	0.091 (0.42)	-0.009 (-0.05)		-0.194 (1.11)	-0.069 (-0.21)
Constant	-2.144 (-1.24)	-0.294 (-0.89)	0.282 (0.77)	67.48 (1.80)*	0.870 (1.55)	-1.591 (-2.27)**
Observations	77					
Observations = 1	11	27	25	65	37	16
Pseudo R-squared	.741	.559	.420	.506	.342	.560
% of correctly classified ⁱ	.935	.883	.844	.870	.779	.896

The probability of being a super-spreader is determined by financial institutions' size. The probability of financial institutions contributing to the 99th percentile of other centrality measures is also determined by size, but some (i.e. \mathcal{H}_i , s_i , and \mathcal{B}_i) by borrowing concentration as well. ^a All independent variables are standard scores of the original variable (i.e. number of standard deviations above the estimated mean), whereas the dependent variables correspond to 1 when the financial institution contributes to the 99th percentile, and zero otherwise. ^b *t*-statistics in parenthesis, significant at .10*, .05** and .01***. ^c Assets' value, as reported by the Financial Superintendence of Colombia (SFC). ^d Debt to assets ratio, based on balance sheet data reported by SFC. ^e Return over assets. ^f Herfindahl-Hirschman index on weighted borrowing counterparties. ^g Herfindahl-Hirschman index on weighted lending counterparties. ^h Borrowing and lending concentration are not reported because the maximum likelihood estimation was unfeasible (i.e. perfect prediction). ⁱ Weighted average of correct classifications of the dependent variable, in which the correct classification of a super-spreader consists of a predicted probability above .5, whereas the correct classification of a non-super-spreader consists of a predicted probability lower than or equal to .5

In this sense, financial institutions do not connect to each other randomly, but they interact based on a size-related preferential attachment process. Such size-related preferential attachment coincides with literature about the role of market power and too-big-to-fail implicit subsidies (e.g. implicit or explicit access to last-resort lending) on the increased likelihood of large financial institutions to appear in both sides (i.e. borrowing and lending) of financial markets, their ability to obtain lower funding rates, and their willingness to engage in riskier activities by means of increasing leverage and risk-taking (see Cocco et al., 2009; Bertay et al., 2013; IMF, 2014). Likewise, the size-related preferential attachment process supports evidence of smaller financial institutions relying on stable borrowing and lending

relationships with large counterparties (see Cocco et al., 2009; Fecht et al., 2011; Afonso et al., 2013).

6. Final remarks

In this paper we find that the Colombian interbank funds market displays an inhomogeneous and hierarchical (akin to a core-periphery) connective structure, in which a few financial institutions fulfill the role of super-spreaders of central bank's liquidity within the interbank funds market. Thus, our research work not only contributes to central banks' efforts to analyze the structure and functioning of interbank funds markets, but also contributes to designing liquidity facilities, implementing monetary policy, and identifying those financial institutions with a systemic role in the corresponding market and other related ones (e.g. sovereign securities, foreign exchange, etc.).

Accordingly, four particular contributions of our research work are worth stating. First, we propose a methodological approach that explores the connective structure of the interbank funds network and identifies those financial institutions that may be considered as the most important conduits for monetary policy transmission and for liquidity spreading among participating financial institutions. In this sense, our approach is able to identify interbank funds' systemically important financial institutions, which should be the focus of financial authorities' efforts for preserving financial stability. Likewise, in the sense of Acharya et al. (2012), the presence of super-spreaders –with market power– could support central bank's virtuous role in the efficiency and stability of the interbank market as credible provider of liquidity to a broad spectrum of financial institutions.

Second, our results support recent findings about the existence of some stylized facts in financial networks, namely an inhomogeneous and hierarchical connective structure that contradicts traditional assumptions in interbank contagion models (i.e. homogeneity, symmetry, linearity, normality, static equilibrium). Confirming the robust-yet-fragile characterization of financial networks by Haldane (2009) entails major challenges for financial authorities contributing to financial stability. For instance, as argued after the crisis (e.g. Kambhu et al. (2007); May et al. (2008); Haldane and May (2011); León and Berndsen (2014)), the most evident challenge comes in the form of focusing financial authorities'

preventive actions on super-spreaders, which requires shifting from institution-calibrated to system-calibrated prudential regulation.

Third, as is the case of interbank funds networks in the U.S., Netherlands and Austria, and consistent with the existence of a core-periphery hierarchy, the Colombian interbank funds network is ultra-small, with an average geodesic distance around two. This not only means that the spreading capabilities of interbank funds network are particularly high, either for liquidity or for contagion effects, but it also suggests that the existence of super-spreaders may alleviate the inefficiencies resulting from the under-provision of liquidity cross-insurance in interbank markets documented by Castiglionesi and Wagner (2013).

Fourth, by means of a probit regression model, we confirm that the probability of being a super-spreader is determined by financial institutions' size in the Colombian case. This concurs with evidence from other countries. Accordingly, size may be the main factor behind the interbank funds network's reported scale-free connective structure and its core-periphery hierarchical organization. Nevertheless, as causality may not be inferred from the probit model, it is uncertain whether size is the driving force (i.e. the cause) behind the connective and hierarchical structure of the interbank funds network, or it is the result (i.e. the effect). Moreover, based on complex adaptive systems literature, it may be the case that size is – simultaneously- the driving force and the result of the interbank funds network dynamics by means of feedback effects.

Further related research work may come in several forms. First, it is imperative to test the robustness of results under stringent financial liquidity conditions, such as a disruption of local or external credit lines, or a contractionary monetary policy; we attempted such test, but available data does not cover periods that could be fair examples of such conditions –for instance, year 2002. Second, the causality in interbank funds networks' dynamics should be explored to understand the role of size and other variables as causes and effects. Third, due to its contribution to money market liquidity, collateralized borrowing should also be considered for identifying central bank's liquidity supers-spreaders.

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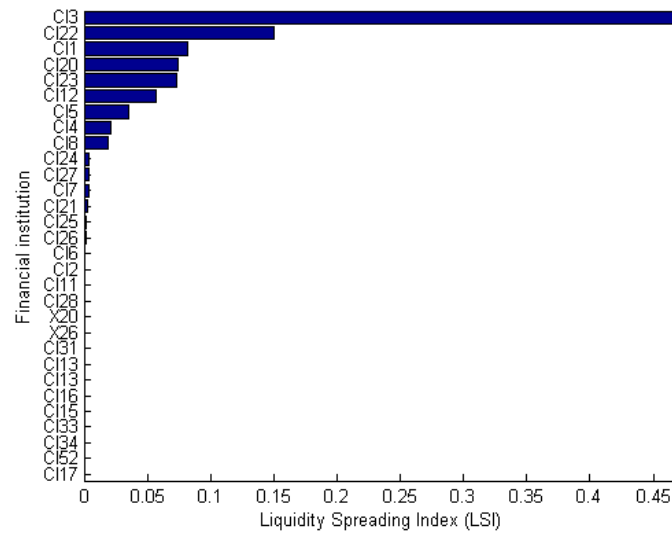
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Appendix 1.

2011



2012

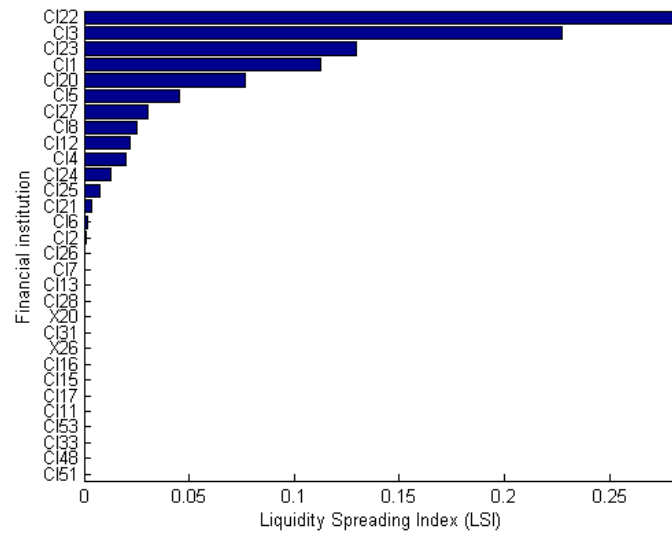


Figure 7. Top-30 financial institutions by estimated LSI_i . Credit institutions (CI) dominate the contribution to LSI . Other types of contributing institutions are other financial institutions (Xs).

Appendix 2.

2011						
	<i>LSI</i>	<i>h</i>	<i>a</i>	<i>k</i>	<i>s</i>	<i>b</i>
<i>LSI</i>	1					
<i>h</i>	0.71	1				
<i>a</i>	0.69	0.41	1			
<i>k</i>	0.41	0.60	0.56	1		
<i>s</i>	0.70	0.48	0.99	0.62	1	
<i>b</i>	0.21	0.34	0.38	0.54	0.43	1

2012						
	<i>LSI</i>	<i>h</i>	<i>a</i>	<i>k</i>	<i>s</i>	<i>b</i>
<i>LSI</i>	1					
<i>h</i>	0.74	1				
<i>a</i>	0.89	0.56	1			
<i>k</i>	0.58	0.73	0.65	1		
<i>s</i>	0.90	0.63	0.99	0.72	1	
<i>b</i>	0.54	0.39	0.66	0.57	0.69	1

2013						
	<i>LSI</i>	<i>h</i>	<i>a</i>	<i>k</i>	<i>s</i>	<i>b</i>
<i>LSI</i>	1					
<i>h</i>	0.64	1				
<i>a</i>	0.83	0.33	1			
<i>k</i>	0.75	0.64	0.75	1		
<i>s</i>	0.88	0.41	0.99	0.80	1	
<i>b</i>	0.78	0.28	0.78	0.64	0.84	1

Figure 8. Linear dependence (correlation) between *LSI* and traditional centrality measures. Liquidity Spreading Index (*LSI*), estimated as in (11); authority (*a*) and hub centrality (*h*) are estimated as in (10); degree (*k*) corresponds to the number of incoming and outgoing links (3); strength (*s*) corresponds to the value (weight) of the incoming and outgoing links (4); betweenness (*b*) corresponds to the extent to which a vertex lies on paths between other vertexes (8).

Appendix 3

Table 3
Standard statistics of variables in the probit model
2013

Variable	Mean	Standard Deviation	Kurtosis	Skewness
<i>LSI</i>	0.013	0.045	26.931	4.636
<i>h</i>	0.013	0.033	13.012	3.187
<i>a</i>	0.013	0.038	27.426	4.595
<i>k</i>	0.013	0.017	7.367	1.860
<i>s</i>	0.013	0.035	32.848	4.979
<i>b</i>	0.013	0.070	63.327	7.676
<i>size</i>	5.68×10^6	14.08×10^6	20.858	3.982
<i>lev</i>	0.844	0.205	6.567	-1.977
<i>roa</i>	0.039	0.070	8.599	-0.222
<i>borr</i>	0.737	0.263	2.210	-0.621
<i>lend</i>	0.270	0.313	3.192	1.099

Liquidity Spreading Index (*LSI*), estimated as in (11); authority (*a*) and hub centrality (*h*) are estimated as in (10); degree (*k*) corresponds to the number of incoming and outgoing links (3); strength (*s*) corresponds to the value (weight) of the incoming and outgoing links (4); betweenness (*b*) corresponds to the extent to which a vertex lies on paths between other vertexes (8); *size* is the asset value in COP million, as reported by the Financial Superintendence of Colombia (SFC); *lev* is the debt to assets ratio, based on balance sheet data reported by SFC; *roa* is the return over assets; *borr* and *lend* are the Herfindahl-Hirschman indexes on weighted borrowing and lending counterparties, respectively. All statistics are estimated based on original variables (i.e. they are not standardized).

Appendix 4

Table 4
Probit regression on selected determinants
2011

Variable ^{a, b}	LSI_i	\mathcal{H}_i	a_i	\mathcal{H}_i^h	s_i	\mathcal{L}_i
Size (size) ^c	4.668 (1.72)*	2.712 (3.18)***	14.373 (1.90)**	8.784 (1.75)*	9.645 (2.03)**	2.806 (2.63)***
Leverage (lev) ^d	5.097 (0.04)	0.732 (1.09)	0.149 (0.22)	-0.147 (-0.74)	0.071 (0.18)	-0.264 (-0.31)
Financial performance (roa) ^e	-7.369 (-0.83)	-0.175 (-0.41)	-0.205 (-0.40)	0.101 (0.59)	-0.250 (-0.76)	0.062 (0.09)
Borrowing concentration (borr) ^f	0.024 (0.04)	-0.910 (-3.42)***	2.013 (1.59)		-0.585 (-2.22)**	-1.188 (2.09)**
Lending concentration (lend) ^g	-1.927 (-1.07)	0.002 (0.01)	-4.994 (-1.29)		-0.858 (-1.84)*	-0.971 (-0.96)
Constant	-8.379 (-1.03)	-0.443 (-1.04)	-1.717 (-1.16)	4.114 (2.09)**	2.492 (1.42)	-1.935 (-2.81)***

Observations	77					
Observations = 1	10	27	18	57	63	13
Pseudo R-squared	.826	.605	.853	.178	.166	.686
% of correctly classified ⁱ	.961	.883	.948	.829	.818	.922

The probability of being a super-spreader is determined by financial institutions' size. The probability of financial institutions contributing to the 99th percentile of other centrality measures is also determined by size, but some (i.e. \mathcal{H}_i , s_i , and \mathcal{L}_i) by borrowing concentration as well. ^a All independent variables are standard scores of the original variable (i.e. number of standard deviations above the estimated mean), whereas the dependent variables correspond to 1 when the financial institution contributes to the 99th percentile, and zero otherwise. ^b *t*-statistics in parenthesis, significant at .10*, .05** and .01***. ^c Asset value, as reported by the Financial Superintendence of Colombia (SFC). ^d Debt to assets ratio, based on balance sheet data reported by SFC. ^e Return over assets. ^f Herfindahl-Hirschman index on weighted borrowing counterparties. ^g Herfindahl-Hirschman index on weighted lending counterparties. ^h Borrowing and lending concentration are not reported because the maximum likelihood estimated was unfeasible (i.e. perfect prediction). ⁱ Weighted average of correct classifications of the dependent variable, in which the correct classification of a super-spreader consists of a predicted probability above .5, whereas the correct classification of a non-super-spreader consists of a predicted probability lower than or equal to .5

Table 5
Probit regression on selected determinants
2012

Variable ^{a, b}	LSI_i	h_i	a_i	h_i^h	s_i	b_i
Size (size) ^c	2.365 (1.73)*	10.523 (1.87)*	3.474 (3.24)***	6.838 (1.33)	11.311 (2.23)**	1.107 (2.86)***
Leverage (lev) ^d	7.503 (0.77)	-0.183 (-0.68)	0.125 (0.45)	0.044 (0.23)	0.118 (0.52)	0.446 (1.04)
Financial performance (roa) ^e	0.932 (0.69)	0.104 (0.10)	-0.190 (-0.84)	0.158 (0.88)	-0.182 (-0.84)	-0.338 (-0.88)
Borrowing concentration (borr) ^f	-0.194 (-0.34)	-2.061 (-2.23)**	0.517 (1.91)*		-0.205 (-0.95)	-0.379 (-1.75)*
Lending concentration (lend) ^g	-0.306 (-0.22)	0.298 (0.51)	-0.339 (-1.08)		-0.387 (-1.58)	-0.257 (-0.88)
Constant	-5.986 (-0.97)	1.463 (-0.84)	0.039 (0.10)	3.431 (1.66)*	3.987 (2.00)**	-0.919 (-3.09)***
Observations	70					
Observations = 1	11	28	22	57	34	18
Pseudo R-squared	.768	.778	.539	.178	.458	.397
% of correctly classified ⁱ	.928	.943	.914	.829	.829	.857

The probability of being a super-spreader is determined by financial institutions' size. The probability of financial institutions contributing to the 99th percentile of other centrality measures is also determined by size, but some (i.e. h_i , s_i , and b_i) by borrowing concentration as well. ^a All independent variables are standard scores of the original variable (i.e. number of standard deviations above the estimated mean), whereas the dependent variables correspond to 1 when the financial institution contributes to the 99th percentile, and zero otherwise. ^b *t*-statistics in parenthesis, significant at .10*, .05** and .01***. ^c Asset value, as reported by the Financial Superintendence of Colombia (SFC). ^d Debt to assets ratio, based on balance sheet data reported by SFC. ^e Return over assets. ^f Herfindahl-Hirschman index on weighted borrowing counterparties. ^g Herfindahl-Hirschman index on weighted lending counterparties. ^h Borrowing and lending concentration are not reported because the maximum likelihood estimated was unfeasible (i.e. perfect prediction). ⁱ Weighted average of correct classifications of the dependent variable, in which the correct classification of a super-spreader consists of a predicted probability above .5, whereas the correct classification of a non-super-spreader consists of a predicted probability lower than or equal to .5